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Ontology-based context modeling for emotion recognition in an intelligent web

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Abstract We describe an ontological model for representation and integration of electroencephalographic (EEG) data and apply it to detect human emotional states. The model (*BIO_EMOTION*) is an ontology-based context model for emotion recognition and acts as a basis for: (1) the modeling of users' contexts, including user profiles, EEG data, the situation and environment factors, and (2) supporting reasoning on the users' emotional states. Because certain ontological concepts in the EEG domain are ill-defined, we formally represent and store these concepts, their taxonomies and high-level representation (i.e., rules) in the model. To evaluate the effectiveness for inferring emotional states, *DEAP dataset* is used for model reasoning. Result shows that our model reaches an average recognition ratio of 75.19 % on *Valence* and 81.74 % on *Arousal* for eight participants. As mentioned above, the *BIO-EMOTION* model acts like a bridge between users' emotional states and low-level bio-signal features. It can be integrated in user modeling techniques, and be used to model web users' emotional states in human-centric web aiming to provide active, transparent, safe and reliable services to users. This work aims at, in other words, creating an ontology-based context model for emotion recognition using EEG. Particularly, this model completely implements the loop body of the W2T data cycle once: from low-level EEG feature acquisition to emotion recognition. A long-term goal for the study is to complete this model to implement the whole W2T data cycle.

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1 Introduction

Web Intelligence (WI) was firstly introduced by Zhong, Liu, Yao, and Ohsuga in 2000 [54], as a joint research effort in developing the next generation Web-based intelligent systems, through combining their expertise in Data-Mining, Agents, Information Retrieval, and Logic.

Broadly speaking, WI encompasses the scientific research and development that explores the fundamental roles as well as practical impacts of Artificial Intelligence (AI), such as autonomous agents and multi-agent systems, machine learning, data mining, and soft-computing, as well as advanced Information Technology (IT), such as wireless networks, grid computing, ubiquitous agents, and social networks, on the next generation of Web-empowered products, systems, services, and activities. The ultimate goal is to develop and build the World Wide Wisdom Web (W4).

The Wisdom Web of Things (W2T) is an extension of the Wisdom Web in the Internet of Things (IoT) [7, 51] age. The "Wisdom" means that each of things in the Web of Things (WoT) [10, 48] can be aware of both itself and others to provide the right service for the right object at the right time and context. Constructing the W2T for the harmonious symbiosis of humans, computers and things in the hyper world [22, 25] requires a highly effective W2T data cycle, namely "from things to data, information, knowledge, wisdom, services, humans, and then back to things" [56]. There are four central functions of a context model in the W2T: (1) user situational context data processing, (2) the derivation of a knowledge set from a context (made up of a set of context properties), (3) the application of the knowledge set to the provision of active services to a user, and (4) the effect of humans on the things around his/her during the process of receiving services. In order to satisfy users, it is essential to consider user's contexts, which are identified as location context, environment context, device context, user information context. These diverse contexts distinctly come from humans, computers and things in the hyper world, which consist of the social world, the physical world, and the cyber world [26, 27]. Humans are the central of the hyper world. It is easy to provide fully dynamic and appropriate services when user's emotions have been understood [34]. The same person may have different emotions in different situations. This actually reflects the basic nature of human beings [33]. Specifically, one of the issues we address is context modeling for emotion recognition.

We have developed a W2T based *Ontology-based Context Model* which enables context definitions to be created with semantics. To model the factors that identify and describe human emotions we have built the novel *BIO_EMOTION* ontology (hereafter termed the *ontology*). The ontology combined with the W2T provides an effective basis upon which human emotions can be modelled and used to improve the targeting of service provision. In order to understand human emotional states and provide active, transparent, safe, reliable services to humans, cognitive functions of the brain should be seriously considered. Such a computational model cannot be realized only depending on the traditional expert-driven approach. According to Brain Informatics (BI) [53, 55] methodology, the whole research process of context modeling can be regarded as a BI data cycle which is implemented by measuring, collecting, modeling, transforming, managing, mining, interpreting, and explaining multiple forms of brain data obtained from cognitive experiment by using powerful EEG equipment.

BIO_EMOTION, an ontology-based context model for emotion recognition, provides a basis for: (1) the modeling of user contexts, including user profile, EEG data, the situation and environment factors, and (2) supporting reasoning on the user's emotional state(s). The ontology is dedicated to *bio-signal,* and is built using the *Web Ontology Language* (OWL) [32] incorporating domain-specific concepts with relevant context properties and literal values. Entities in the ontology include: *situation*, *mood*, and *bio-signal* features, etc. The ontology acts like a bridge between a user's dynamic situation with his/her emotion(s) and low-level biomedical signal features.

The focus of the ontology is on modeling low-level biometric features and mapping such low-level information to high-level human emotions; thus the context model can be used to provide active and reliable services for individuals or communities in the *intelligent* or *smart* hyper world. This work aims at, in other words, creating an ontology-based context model for emotion recognition using EEG. Particularly, a feature of this model is that it can eventually complete the process that the loop body of the W2T data cycle is fully executed once: from low-level EEG feature acquisition to emotion recognition. In this study, the C4.5 algorithm [40] is used to predict emotional states. Experimental result based on DEAP database shows that recognition of human emotions on two dimensions (Valence and Arousal) reaches average classification rate of 75.19 % and 81.74 %.

The remainder of this paper is organized as follows. Section 2 sets out an overview of related research with the focus on context modeling of emotions. Section 3 presents the BIO-EMOTION model, in which an analysis of physiological signal features, particularly low-level EEG features, is presented with the implementation of ontology. The application of the ontological rule-based inference using the DEAP dataset [21] is described in Section 4. Section 5 sets out a discussion and future work with open research questions and challenges considered. Finally, section 6 gives a conclusion.

2 Related work

Recent research addressing context modeling has investigated a broad range of approaches and there has been a significant increase in number of attempts to build context models including emotions and affect factors.

Emotion is a complex aspect. In this sense, theories of emotions proposed by cognitive psychology are a useful starting point in order to describe emotion. Carofiglio and de Rosis [5] in "*Combining Logical with Emotional Reasoning in Natural Argumentation*" consider the effect of emotions on an argumentation in a dialog; how emotions are activated and how the argumentation is adapted accordingly using Belief Networks is modelled. In their model the user interacting with the system's agent is represented as the receiver. González et al. [16] carried out one of the first investigations of affective modeling in recommender systems. They built the smart user model, a data structure based on users' emotional intelligence. However, they did not provide sufficient information to assess the success rate of their approach.

Conati' [9] presents a probabilistic context model based on *Dynamic Decision Network* which represents the emotional state of the user interacting with an educational game along with h/her personality and goals. ABAIS, created as a rule-based system by Hudlicka and McNeese [18], assesses pilots' affective states and active beliefs and takes adaptive precautions to compensate for their negative effects. Klein et al.'s [20] interactive system responds to the user's self-reported frustration during an interaction with a computer game. All these systems are created to adapt to the user's affective state based on the current context,

however none of them performs any emotion recognition stage and they don't precisely represent concepts associated with emotions.

Mandryk [30] used a fuzzy logic approach to model human emotions. Some rules in his model were built in order to convert physiological variables into arousal and valence and some rules for transforming arousal-valence space into five emotional states. These rules just use the nominal attributes: *low, middle and high*, but they do not include any numeric ones. Thus, it will be inaccurately quantified and then affect the emotion evaluation.

In relation to ontology of emotions, there are diverse valid research initiatives in distinct application fields (e.g. Mathieu [31]; Francisco et al. [13]; López et al. [23]) and, additionally, there is a W3C Emotion Markup Language Incubator Group, working on the definition of valid representations of those aspects of emotional states that appear to be relevant for a number of use cases in emotion scenarios.

In text analysis area, Mathieu [31] presented a semantic lexicon in the field of feelings and emotions. This lexicon is described with an ontology. Words in the lexicon are emotionally labeled as positive, negative and neutral. With the support of ontology technologies, users can retrieve information in a semantic manner [8]. Focusing on speech, Galunov et al. [15] presented an ontology for speech signal recognition and synthesis where emotion is taken into account. On the other hand, focusing on the context, Benta et al. [3] presented an ontology-based representation of the affective states for context aware applications which allows expressing the complex relations between affective states and context elements. Although these kinds of approaches have relevance in their respective fields, they lack properly expression of the multimodal nature of human emotions [24]. In this sense, Cearreta et al. [6] modeled user context by dividing it into several parts and focusing on emotion-related aspects in each part.

Brain signals seem to reflect the "inner" and real emotions. Currently there is little EEG-based research in the ontological modeling area, although a variety of statistical techniques are emerging for analysis of spatiotemporal patterns in EEG research [11]. According to Frishkoffet al. [11], they introduced a framework for mining ERP (event-related potentials) ontologies based on clustering, classification and association rule mining. Their goal is to address basic scientific questions in ERP research using ontology-based classification. On the one hand, we referred to Frishkoff's methods for classifying and labeling brain signal patterns which can lead to refinement of these concepts and association rules. On the other hand, we linked the low-level EEG features to a high-level human emotional feature. Specifically, we labeled EEG features for individual participants, identified important metrics for emotion recognition and defined the rules showing corresponding relationships between EEG and emotions in the BIO-EMOTION model. Given the above, an ontology-based context model for describing emotion is proposed and can complete the process that the loop body of the W2T data cycle is fully executed once: from low-level feature acquisition to emotion recognition.

3 The BIO-EMOTION ontology

The BIO-EMOTION ontology is the development of an intelligent *contextual* and *affective* model capable of accommodating a range of diverse environments. The ontology provides an upper ontology which captures concepts (OWL classes), context properties, and the related data (*Literal Values*) that identify and describe the EEG information such as *brain region*, *electrodes* and *biometric* features. The context ontological model can be also reused in the same application domain or extended to the domain of interest. The model attempts to

express the relations between bio-signal information and human emotions to help people adjust his feelings.

3.1 Overview of *ontology*

Ontology has traditionally been considered to be a branch of philosophy known as metaphysics where an ontology is a systematic account of existence [17]. In general, an ontology can be defined as the formal specification of a vocabulary of concepts and the relationships among them in a specific domain. In traditional knowledge engineering and in emerging Semantic Web research, ontologies play an important role in defining the semantics of data. The use of ontology in computer science can be traced to Artificial Intelligence (AI) research in the 1960's [44]. Ontology defines a set of representational terms that associate the names of entities (e.g., classes, relations, functions or other objects) in an area of interest (universe of discourse) in a human-readable formalism describing meaning and formal axioms that constrain the interpretation with well-formed use of the terms. In computer science and information systems, an ontology is a representation of a knowledge model with semantic detail and structure.

Formally, ontology is a statement of logical theory to represent objects (e.g., entities) and enable inference and reasoning thereby providing the basis upon which a degree of computational intelligence can be realized. An important concept that underpins the concept of ontology is semantics and semantic relationships between objects and entities.

Ontologies are described as Web services in a machine readable formalism [36] to enable reasoning and inference over the data they expect as input and return as output (which have the characters of W2T proposed in [56]) based on entailment and subsumption. Once Web services are described semantically it allows for large parts of the Web service usage process to be automated. Apparently, a potential issue lies in the failure on some system designers who had attempted to bring more meaning to web resources but without a solid formal underpinning. However, suitable rules can be defined to transform the separated ontological knowledge into a relational network.

3.2 The structure of the BIO-EMOTION ontology

Ontology-based context modeling of data "transforms" things from real world into "data" world, which is one part of W2T data cycle. However, the process of conceptual data modeling in the BIO-EMOTION, as the main body of cycle system, represents various data entities and relationships for the data organization, storage and expression. Besides, we need a more natural way of extracting user's emotions in cyber world. Actually, an interruption in human-computer interaction, with the purpose to explicitly ask user about his current feeling could modify true feeling of user. Such interruption should be avoided by a suitable approach, i.e. a continuous extraction of actual affective state of user by a mechanism of interpretation and thus without explicit asking for consciously experienced emotion [49]. It has been shown that emotional markers are presented in EEG signals. As brain signals can be hardly deceived by voluntary control and are available all the time, without needing any further action of the user, we focus on creating a model for emotion recognition and using EEG signals as context information. Accordingly, one challenge, at this stage of the ontology development, is to develop and test a framework for separating, expressing and classifying complex patterns that are superposed in measured EEG. Some general concepts (i.e., linear features of EEG) and rules (i.e., the high-level concept representation) will be described in the model. Ontology construction consists of two steps: the process from

perception of a situation or context or user's physiological information to derivation of a knowledge set; from the knowledge set to provision of emotion reasoning results. The former requires mechanisms to extract, retrieve, and analyze data/information along the time axis or at a certain time section, and then represent them into the ontology in the form of logical expression. As shown in [56], the model includes different levels of technology. It models data by different dimensions and has various specifications on the different levels of conversion mechanism.

1. The first and indispensable one is the level of conceptual entity. This level is primarily involved with information extraction and knowledge expression of things coming from physical world. Human knowledge expression is implemented in the ontology which consists of 84 classes and 38 property definitions. Figure 1 shows a representation of some key *Entities* defined in the ontology. The key top-level elements of the ontology consist of classes and properties that describe *#Emotion*, *#User*, and *#Situation* concepts (OWL classes) with <*hasEEGFeature*> and <*hasEmotion*> properties. A description of the principal classes and their functions is as follows:

   - The #***Emotion*** class: This class defines the state of a user's affective state(s). The two main opposite approaches are discrete (e.g. labels like joy, anger, fear, sadness, frustration, etc.) and dimensional (mainly the valence-arousal space): (1) the discrete emotions are used when we search to match a specific state of the user, like frustration; (2) the affective dimensions are continuous, and so have been used more for real-time monitoring of user emotion. Moreover, the dimensional mode of

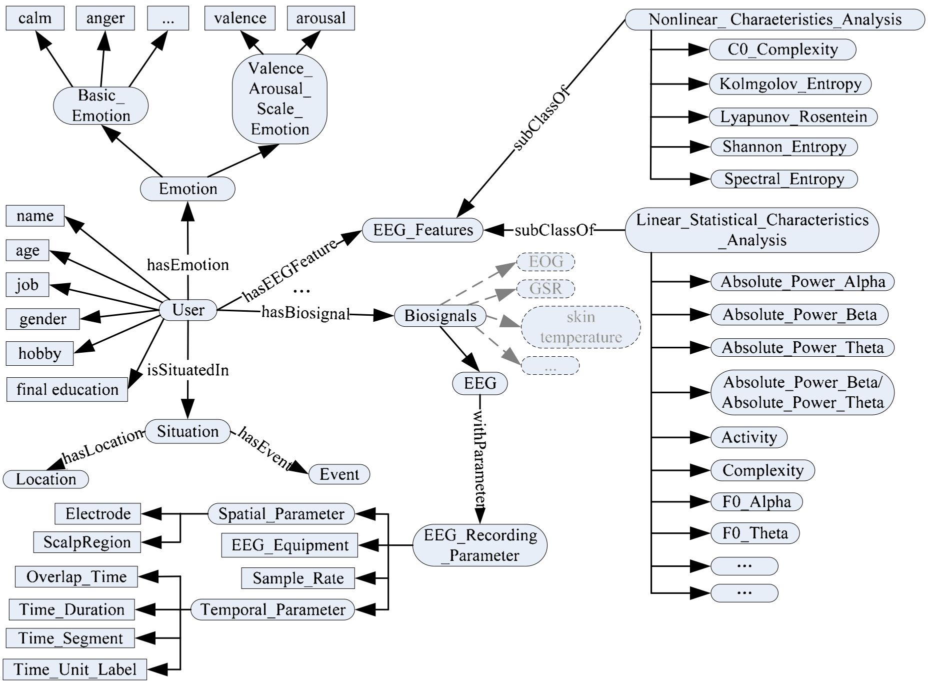

Figure 1 The BIO-EMOTION ontology mainly concerned with EEG context. Each rounded rectangle with *solid arrow* represents an OWL class.

representation allows the computation of dynamics in the state of the user, which is needed to represent emotion as an evaluative process. According to a widely accepted view, a simple yet effective theory employs a bidirectional emotion model defined by two basic parameters/variables: (a) the affective degree of *"pleasantness/valence"*, and (b) *"arousal"*. The two-dimensional emotion plane can be divided into four quadrants (HVHA, HVLA, LVLA, and LVHA) as shown in Figure 2. Thus, each emotional state can be defined as some combination of the valence and arousal components [4, 43]. We can analyze emotions from the above two approaches: discrete affective states through *#Basic_Emotion* class and the combination of the valence and arousal dimensions through *#Valence_Arousal_Scale_Emotion* class. The concept *#Basic_Emotion* detects individual emotional states, such as joy, distress or fear. The concept *#Valence_Arousal_Scale_Emotion* focus on two dimensions of nine points each (1–9): valence (ranging from positive to negative or unpleasant to pleasant) and arousal (ranging from calm to exciting).

- The #***Biosignals*** class: Physiological signals are known to include emotion information that can be used for the assessment of emotions. They comprise the signals originating from the central nervous system. Additionally, using these signals has advantages over other methods: (1) they are relatively robust where involuntary control is concerned, and (2) are available *anytime-anywhere* without active user input. Therefore, EEG signal is recorded and processed as subclasses of *#Biosignals* class to enable an analysis of human emotion(s) and affective state(s). The multi-aspect brain data analysis is implemented to combine human brain signals and data analysis methods for understanding complex brain data in depth, in order to uncover the emotion reactivity of thinking centric cognitive functions. The ontology has been designed to contain other *physiological* signals including: electrooculogram (EOG), skin temperature and peripheral physiological signals including GSR, respiration amplitude, electrocardiogram(ECG), blood volume, electromyograms (EMG) of Zygomaticus and Trapezius muscles, etc. Such signals are not addressed in this paper, which will be studied in our future work. These signals represent potentially profitable directions for future research of BIO-EMOTION.
- The #***Situation*** class: This class describes an important context in the ontology. The analysis of human emotions will be more accurate when combined with user's context as context is influential in the fluctuation of psychological signals and also enhances the performance of autonomous emotion detection [47]. The context in the model is a very broad concept, including any information about the user's location,

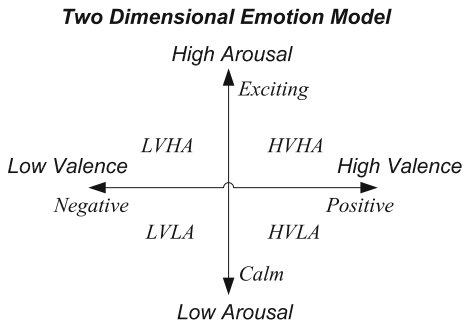

Figure 2 Visualization of the emotion model. Pictures in the 2-D emotional space are defined by the valence and the arousal dimension.

time, physical and social environment and the device being used, etc. The *#Situation* class defines an individual's spatio-temporal state in terms of conditions, circumstances, and proximate information which are very important clues to effective modeling. Hence, the class describes the context such as the whereabouts of the user (*#Location*) and what happens to the user (*#Event*), etc.

- The *#**User*** class: Emotions are highly dependent on users, and we cannot give a precise detection of the specific underlying emotion even if external environment, as an impact factor, is seriously considered. It is vital that the context model is aware of users' demographic characteristics ranging from the very basic features such as: *gender*, *age* or *native language* to more complex socio-cultural parameters including: the *level of formal education* and *family income*. The *#User* class is incorporated into the ontology to hold the demographic parameters with their related *Literal Values*.

2. The wisdom level. The BIO-EMOTION describes things from physical world as different conceptual entities and entity hierarchical relations. Meanwhile, the specific values of these entities are built into the model as attribute values. Thus the model constructs concepts, attributes and instances of concept according to the semantics of these things. Ontology is the key technology behind Semantic Web for making information more meaningful by adding knowledge in a non-hierarchical structure. In such an environment, BIO-EMOTION is used to uniquely describe context, which gives a common semantic understanding of the context information.
3. The service level of technologies is involved with service construction and service integration. The model creates a recommendation or service according to user's contexts which include his emotions and emotional responses.

The above modeling technique depicts the processes of transforming the data of things into an integrated conceptual model and providing reliable services to humans. Particularly, user's feedback is also an indispensable in this application. Upon receiving user's feedback the model tries to refine the relations between different entities. Whenever user's feedback is input, the model adapts services for improving quality of services and satisfying users. A goal of BIO-EMOTION is to realize the harmonious symbiosis of humans, computers, and things in the emerging hyper world. Obviously, the whole context modeling implements a W2T data cycle: from things to context model, services, humans, and then back to things.

3.3 Context reasoning

The recognition of a user's emotional state in intelligent systems has historically two approaches: (1) direct user interviews, or (2) rule-based approach often with predicate logic or other classic AI reasoning techniques (especially the approaches used in pattern recognition). It has been recognized that advanced reasoning capabilities require integrating all the human-level capabilities such as robustness, autonomous interaction with their environment, communication with natural language, planning, learning, discovery and creativity. Many of the reasoning components can provide more sensitive and objective metrics for emotion recognition when compared with user's verbal responses in interviews [50]. We use the second approach in our model inference for it integrating various factors to achieve a proper goal.

The ontology offers representation and reasoning possibilities on human EEG signals and can be equipped with formal semantics. For a given emotional task undertaken by one user,

the system initially generates a decision tree using the features available in the training data. All of these low level bio-signal features are explicitly represented as concepts in the context ontology. To finish the reasoning, the low-level context should be converted to high-level context according to the context model and inference rules. The inference rules are composed of the OWL axiom semantic component. The rule base contains the horn logic-formed rules which are formed by clauses according to First-Order Logic. The OWL axiom is used to infer the uncertainly-defined relations or meanings between users' emotions and contexts. The semantic rules derived by the C4.5 algorithm are employed in the emotion recognition task. The model's inference rules describe personalized emotional information which consists of users' physiological signal status, the proper combination of physiological features, emotional states and personal information.

4 Model instantiation

In this section, we describe the approach adopted to associate low-level EEG features with human emotional states in the context model. The dataset DEAP [21] incorporating multimodal physiological signals is used in our research to analyze human emotions. These physiological signals include Galvanic Skin Response (GSR), EEG, respiration amplitude, skin temperature, electrocardiogram (ECG), blood volume by plethysmograph, electromyograms of Zygomaticus and Trapezius muscles, and electrooculogram (EOG). Among these variable signals, the brain can be seen as the origin of emotion. It has been shown that emotional markers are present in EEG signals. Simultaneously, most cognitive processes take place within a few hundred milliseconds, so fine-grained representation of the time course of brain activity is extremely important. In addition, with the advent of dense-array methodologies, modern EEG methods are now characterized by high spatial (scalp topographic), as well as high temporal dimensionality. As mentioned above, we mainly evaluate EEG signals in our preliminary study.

We firstly got the raw EEG data from the dataset and extracted various statistical, linear and nonlinear features from each frame. Since the amount of feature data extracted was extremely large (*the curse of dimensionality problem*) we performed *dimensionality reduction* using F-score. Finally, feature vectors were used to generate rules with human emotions as consequent parameters of these rules, these vectors obtained by using the C4.5 algorithm [40].

4.1 Data collection and pre-processing

EEG and peripheral physiological signals coming from 32 healthy participants were recorded using a Biosemi ActiveTwo system[1] on a dedicated recording PC (Pentium 4, 3.2 GHz). EEG was recorded at a sampling rate of 512 Hz using 32 active AgCl electrodes (placed according to the international 10–20 system) [21]. The 40 videos were presented in 40 trials, each consisting of 1 min display of the music video and self-assessment for arousal, valence. The arousal and valence scales are from 1 to 9. The valence scale ranges from unhappy or sad to happy or joyful. The arousal scale ranges from calm or bored to stimulated or excited. Two different binary classification problems were posed: the classification of low/high arousal and low/high valence. To this end, the participants' ratings during the experiment are used as the ground truth. The ratings for each of these scales are divided into

[1] http://www.biosemi.com

two classes (low and high). On the 9-point rating scales, the threshold was simply placed in the middle.

Brain data represents a mixture of "signal" (functional brain patterns) and "noise". Data decomposition methods can help separate signal from noise and disentangle overlapping patterns. A *Bandpass* filter was used to smooth the signals and eliminate EEG signal *drifting* and EMG *disturbances* [38]; a Wavelet Algorithm eliminated EOG disturbances [37]. The raw signals were trimmed to a fixed time length of 60 s. Features were extracted by sliding 4-second windows with a 2-second overlap. We computed EEG features from different approaches:

(1) The time and frequency domains (e.g., power spectral density, peak alpha frequency, Hjorth parameters, center frequency, etc.);
(2) Statistics (e.g. mean value, standard deviation, skewness, kurtosis, etc.);
(3) Nonlinear dynamics domains (e.g., C0-Complexity, Shannon entropy, kolmgolov entropy, the largest lyapunov exponent, etc.).

If all EEG features on 32 electrodes are analyzed in each reasoning process, it will generate an enormous amount of computing, so typical feature values were computed merely on 11electrodes according to [21, 39, 45].

For each approaches we normalized each feature by subtracting its minimum value and dividing the difference by the range of the attribute and then multiplying by 10. Then F-score, a feature selection filter method, was used to measure the discrimination of different sets of real numbers. Given training vectors x_k, $k=1,2,\ldots,m$, if the number of high valence and low valence are $n_{highvalence}$ and $n_{lowvalence}$ respectively, then the valence F-score of the *i*th feature is defined as:

$$F(i) \equiv \frac{\left(\overline{x}_i^{(highvalence)} - \overline{x}_i\right)^2 + \left(\overline{x}_i^{(lowvalence)} - \overline{x}_i\right)^2}{\frac{1}{n_{highvalence}-1} \sum_{k=1}^{n_{highvalence}} \left(x_{k,i}^{(highvalence)} - \overline{x}_i^{(highvalence)}\right)^2 + \frac{1}{n_{lowvalence}-1} \sum_{k=1}^{n_{lowvalence}} \left(x_{k,i}^{(lowvalence)} - \overline{x}_i^{(lowvalence)}\right)^2} \tag{1}$$

where $\overline{x}_i$, $\overline{x}_i^{(highvalence)}$, $\overline{x}_i^{(lowvalence)}$, are the average of the *i*th feature of the whole, high valence and low valence emotional data sets, respectively; $x_{k,i}^{(highvalence)}$ is the *i*th feature of the *k*th high valence instance, and $x_{k,i}^{(lowvalence)}$ is the *i*th feature of the *k*th low valence instance. The numerator indicates the discrimination between the different emotion sets, and the denominator indicates the one within each of the two sets. The larger the F-score is, the more likely this feature is more discriminative. Features marked as irrelevant are simply removed from the training set. The arousal F-score of the the *i*th feature is the same as valence one, which is defined as:

$$F(i) \equiv \frac{\left(\overline{x}_i^{(higharousal)} - \overline{x}_i\right)^2 + \left(\overline{x}_i^{(lowarousal)} - \overline{x}_i\right)^2}{\frac{1}{n_{higharousal}-1} \sum_{k=1}^{n_{higharousal}} \left(x_{k,i}^{(higharousal)} - \overline{x}_i^{(higharousal)}\right)^2 + \frac{1}{n_{lowarousal}-1} \sum_{k=1}^{n_{lowarousal}} \left(x_{k,i}^{(lowarousal)} - \overline{x}_i^{(lowarousal)}\right)^2} \tag{2}$$

Therefore, we used this score as a feature selection criterion. In our experiment, the threshold value was set at 3.301122 on both valence and arousal dimensions.

For the purpose of getting higher emotion recognition, we used a discretization method *PKIDiscretize* in the Waikato Environment for Knowledge Analysis (WEKA) after F-score feature selection. The next step is constructing the inference rules based on C4.5 algorithm, which is detailed in the next subsection.

4.2 Rule-based inference

A core of BIO-EMOTION mentioned above is ontology mapping including entity integration and knowledge expression because all of physical things such as brain data should be "translated" as ontological resources by database based [52] or Web based [1, 2] ontology technologies. The ontology relies on well-defined context information definitions to arrive at the correct emotional state(s). Another core, mentioned in this section, is ontology inference involved with concept extraction, relation discovery (taxonomic relation discovery [12, 35], non-taxonomic relation discovery [28, 29]), and axiom acquisition [46]. In the BIO-EMOTION model, ontology inference on human emotions from brain data and other contexts mainly focuses on concept extraction and non-taxonomic relation discovery. The inference provides a holistic knowledge framework to integrate the knowledge about multi-aspect brain data analysis and other contexts for deducing affective states. Based on the analysis corresponding to the data dimensions, methods for data mining and reasoning are deployed for discovering useful knowledge to understand human emotion related to the central nervous system in depth. Inference rules deal with collected information by referring to the stored facts in the ontology. The capabilities for automated classification and establishing relations between concepts provide a bridge between an unrestricted input and a restricted set of concepts. When the reasoner receives user's EEG signal data and his context factors, a context-based reasoning engine generates the query as rules to generate the correct results.

The upper-level technologies provide tools for embedding *description logic* (DL) into ontologies, representing rules and, finally organizing the trust-based infrastructure where the information is discovered and constructed automatically. Inference rules in this case are based on a number of EEG features and other contexts defined as *Classes* in the ontology. A decision list generated from a decision tree is a set of IF-THEN statements. In our research, the user's EEG features and other information are routed down the tree according to the values of the attributes in successive nodes. When a leaf is reached a rule is generated according to the specific emotion assigned to that leaf. The C4.5 algorithm is used in our research to generate rules. The principal motivating factors for use of the C4.5 algorithm include:

- The algorithm merely selects features which are most relevant to differentiate each affective state;
- The algorithm is a rule-based reasoning method and is searched sequentially for an appropriate *if-then* statement to be used as a rule [14].

Using 'rich' input, the ontology applies the C4.5 algorithm to deduce a user's emotions. We have identified the most significant EEG features by pre-processing methods mentioned above to avoid redundant rules. The EEG features from each individual are used for generating personalized affective classification rules by the J48 classifier (a Java implementation of C4.5 Classifier) in WEKA. The confidence factor used for pruning is set at [C=0.25], whereas the minimum number of instances per leaf is set at [M=2]. The classification rules reach an average classification rate of 75.19 % on valence and 81.74 % on arousal based on a 9-fold cross validation. Containing lots of EEG information (electrodes, feature names and the values, etc.), user information (age, vision and level of alertness, etc.) and other contexts (EEG device, experimental time, etc.), each rule is generally extremely long. A simplified example of a tree generated by C4.5 is depicted in Figure 3. The example has omitted a large number of EEG information which has the same structures in a rule, but it

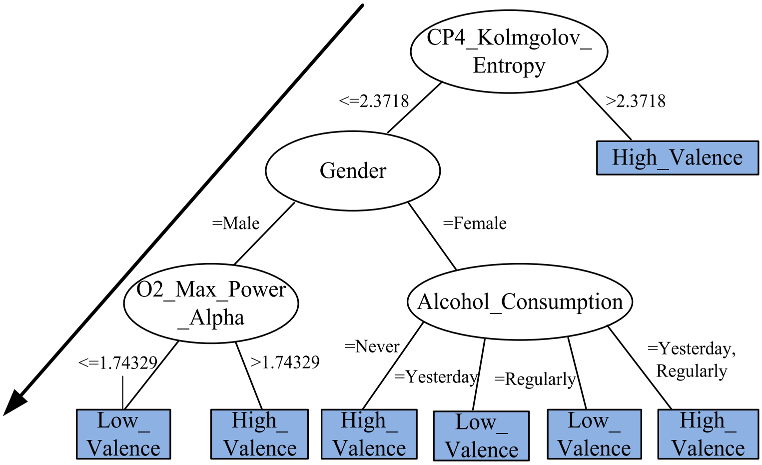

Figure 3 A simplified rule-based decision on valence in the BIO-EMOTION Ontology.

can give a clear understanding of the inference rules. A rule, with its IF-THEN structure defines a basic fact about user's current emotional state. An inference rule generated from the ontology corresponding to Figure 3 is depicted as follows:

```
String rule =
"[Rule1:(?EEG_feature1 rdf:type base:Kolmgolov_Entropy)
 (?EEG_feature1 base:hasValue ?value1)
 lessThanOrEqual(?value1, 2.3718)
 (?EEG_feature1 base:onElectrode ?electrode1)
 (?electrode1 rdfs:label "CP4")
 (?variable1 rdf:type base:Gender)
 (?variable1 base:hasValue ?value2)
 equal(?value2, "Male")
 (?EEG_feature2 rdf:type base:Max_Power_Alpha)
 (?EEG_feature2 base:hasValue ?value2)
 lessThanOrEqual(?value2, 1.74329)
 (?EEG_feature2 base:onElectrode ?electrode2)
 (?electrode2 rdfs:label "O2")
 (?emotion rdf:type base:Emotion)
 (?emotion base:has Symbol "1") ->
 (?user base:hasEmotion ?emotion)]".
```

Variables in a reasoning rule represent the resources (the value of user's EEG features, the name of the EEG features and electrodes that the feature comes from, etc.) which are found using SPARQL queries running on the ontology. The model descriptions and rules in the demonstration are serialized in XML/RDF (as defined in the BIO-EMOITON OWL file

produced by the Protégé 4.1 editor). The namespace identified by the URI-Reference http://www.w3.org/2000/01/rdf-schema# is associated with the prefix 'rdfs'. We also use the prefix 'rdf' to refer to the *RDF* namespace http://www.w3.org/1999/02/22-rdf-syntax-ns#. [41] The vocabulary *'base'* is defined as the namespace of BIO-EMOTION. Each component of a rule is based upon the idea of making statements about resources (in particular *Web resources*) in the form of *subject-predicate-object* expressions. These expressions are known as *triples* in RDF terminology. [42] The *subject* denotes the resource, and the *predicate* denotes traits or aspects of the resource and expresses a relationship between the subject and the object. For example, a *subject* denotes "EEG_feature1" in the first row of the above rule, a *predicate* denoting "has the type of", and an object denoting "Kolmgolov_Entropy".

Particularly, when a user's new EEG features and other contexts are input into the ontology his emotions can be deduced by finding a path from the tree based on the values of context information. Figure 3 shows routing down the decision tree according to the arrow, and when the leaf is reached the user's one emotional dimension, *Valence*, is obtained according to the *Low_Valence* node assigned to the leaf. In a scenario, when an elderly participant is watching a documentary in the bedroom, the raw EEG is detected directly from sensors. Obviously, high-level emotional context cannot be directly acquired from sensors; it is reasoned from the low-level context such as raw EEG data, personal information and environmental information. The BIO-EMOTION demonstrates the key feature of the ontology-based context model. Inference rules are powerful for reasoning with context knowledge. Here, when the elderly participant is watching a violent scene in that film, his corresponding EEG feature values are: "CP5_Kolmgolov_Entroy = 2.447, Cz_Mobility = 0.8032, O2_F0_Beta = 3.987", and some other context are: "Alcohol_Consumption = 2 and Tobacco_Consumption = 1." (Here, '2' in 'Alcohol_Consumption' indicates that the participant consumed alcohol yesterday. '1' in 'Tobacco_Consumption' indicates that the participant never consumes tobacco.) This data can be classified assumedly into the *Low_Valence* emotion concept by checking existing rule sets.

Inference on the context model is graphically modeled in Figure 4. The *Ontology Manager* is the core element that implements the entire process of reasoning on the model. The role of Data Pre-processing is to aggregate various context information into BIO-EMOTION and process EEG de-noising. Ontology-based Reasoning generates user affective states according to inference rules which have been stored in *Ontology Storage*.

Jena [19], a Java API for Semantic Web applications, provides the Ontology-based Reasoning with a set of APIs by which in-memory models of ontology can be created and managed. *Other Situation/Context* represented in Figure 4 contains other types of context: electrodes used in measurement, scalp regions and EEG device, etc. EEG data in our model is the primary context information. The approximate affective state is obtained based on the information mentioned above (user profile, EEG features, situation and the inference rules). Finally, the deduced emotion result is added back to the ontology model as a new axiom.

5 Discussions and future work

In this paper, we have proposed an innovative ontology-based context model for emotion recognition using brain informatics. We succeeded in expressing context of emotions by *Ontology* and applying rules for inference. We also realized a combination between emotion recognition based on physiological signal and ontological modeling of them. However, some drawbacks still exist in our modeling. Here, we give a discussion on both the highlights and drawbacks of BIO-EMOTION.

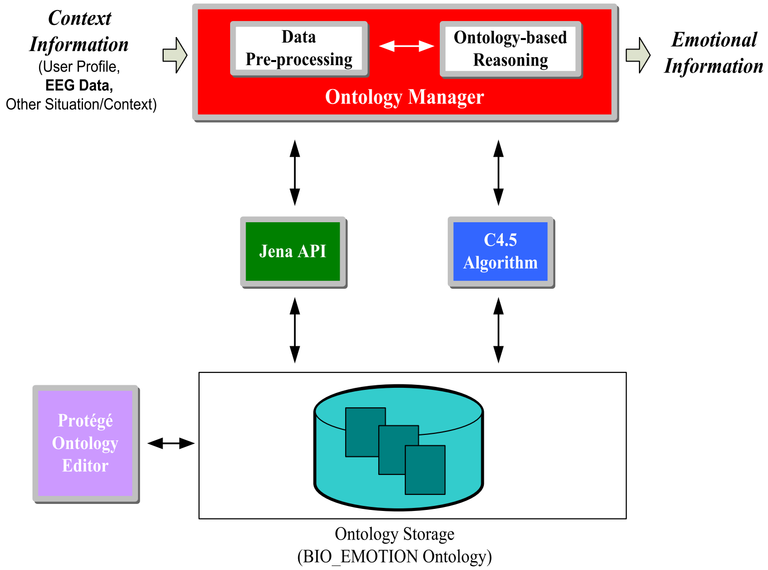

Figure 4 Reasoning on the BIO-EMOTION Ontology model.

– The BIO-EMOTION modeling is a core issue of W2T study. For supporting W2T study, a context model of human emotions drawn from brain data, called BIO-EMOTION, is proposed with multiple contexts to be considered. Under this framework, emotion becomes a measurable and analyzable entity, especially for some intelligent Web applications. The model realizes a systematic mapping analysis from low-level brain information to human emotions and supports the BI study, not just data description and data organization. The W2T based brain studies is also a global BI research platform. In our research, the BIO-EMOTION is designed to drive a W2T data cycle, which has achieved the essential part in the whole cycle from things, like low-level EEG signals, to reflection of human affective states. A small sub-process *Human to Things* has not been achieved in our studies for the limitation of the public dataset. We will, at the next step, complete this model to implement the whole data cycle.
– This model is highly informative for the storage of the semantics of the concepts and relations. Domain-specific concepts in BIO-EMOTION are linked to basic or foundational terms in cognitive neuroscience field. Figure 1 gives a proper demonstration of context descriptors in hierarchies which can facilitate both the representation and reasoning about the descriptors. The discovered rules are used for specifying the properties and their precise relationships with defined classes. Giving the mapping rules, once a new data or query comes in, these rules can be searched for answers to the query, which avoids time consumption on repetitively searching in various databases. With further refinements to our model, we will be able to apply this model to automatically label and store existing semantics. Through the creation of reasoning rules within the entailment of first-order logic, a wide range of higher-level, conceptual context such as "what are the participant's affective states when he watches the video called *May It Be* by *Enya*?" can be deduced from relevant low-level context.
– We used the C4.5 algorithm to classify participants' emotional states based on low-level physiological features and reached an average classification rate of 75.19 % on Valence and 81.74 % on Arousal. Furthermore, the classification rules derived from the decision

tree are used to describe the relationships between EEG and human emotions. The next phase of the BIO-EMOTION is focused on result evaluation, that is, identification of errors in emotion classification and data processing. For example, in the present works, the features selected through F-score are also mixed with noise. Although F-score results suggest refinements to the data reduction process, some other metrics that capture attributes more accurately may reduce the computational cost of reasoning.

6 Conclusions

In this paper, we introduce a novel approach to the context modeling of users' emotions and emotion recognition based on EEG. The aim of this research is to create an ontology-based context model to complete the process that the loop body of the W2T data cycle is fully executed once: from low-level EEG feature acquisition to emotion recognition. Emotions become a measurable and analyzable entity, especially for some intelligent Web applications. A realistic use case illustrated how the BIO-EMOTION can be used for emotion recognition. This shows the usefulness of the proposed modeling method. Our research contribution is an ontology-based context model to represent human emotions and related emotional states predicated on EEG signals, which is used in an intelligent Web. The model exploits the relationships among different context attributes, together with its corresponding context management approach to strengthening the flexibility and intelligence. Based on such a model, the further dynamic service can be provided in a flexible and intelligent way. The development of ontologies may be central to addressing these problems. Indeed, adoption of ontologies has already enabled major scientific progress in biomedical research and is a rapidly growing area in bioinformatics and neuro-informatics research. We expect that our BIO-EMOTION ontology will be extended to other types of neuroscience data and to support other biomedical ontology-based data sharing efforts.

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References

1. Astrova, I.: Reverse Engineering of Relational Database to Ontologies. The Semantic Web: Research and Applications First European Semantic Web Symposium, pp. 327–341 (2004)
2. Astrova, I., Stantic, B.: Reverse Engineering of Relational Databases to Ontologies: An Approach Based on an Analysis of HTML Forms. Proc. the Workshop on Knowledge Discovery and Ontologies at ECML/PKDD, pp. 73–78 (2004)
3. Benta, K. L., Rarău, A., Cremene, M.: Ontology based affective context representation. In: Proceedings of the 2007 Euro American conference on Telematicsand information systems (EATIS'07). Faro, Portugal (2007)
4. Busso, C., Deng, Z., et al.: Analysis of emotion recognition using facial expressions, speech and multimodal information. Proceedings of the 6th International Conference on Multimodal interfaces. State College, PA, USA, ACM: 205–211 (2004)
5. Caroglio, V., de Rosis, F. d.: Combining logical with emotional reasoning in natural argumentation. In: Conati, C., Hudlika, E., Lisetti, C. (eds.) The UM'03 Workshop on Affect, Pittsburgh (2003)
6. Cearreta, I., López, J.M., Garay, N.: Modelling multimodal context-aware affective interaction. In: Proceedings of the Doctoral Consortium of the Second international conference on Affective Computing and Intelligent Interaction (ACII 2007), pp. 57–64. Lisbon, Portugal (2007)

7. Chaouchi, H.: The Internet of Things-Connecting Objects to the Web. ISTE Ltd.Wiley, New York (2010)
8. Chi, Y.-L., Peng, S.-Y., Yang, C.-C.: Creating Kansei engineering-based ontology for annotating and archiving photos database. In: Jacko, J. (ed.) Human-Computer Interaction, Part I, HCII 2007, LNCS vol. 4550, pp. 701–710. Springer (2007)
9. Conati, C.: Probabilistic assessment of user's emotions in educational games. J. Appl. Artif. Intell. **16**(7–8), (2010)
10. Dillon, T., Talevski, A., Potdar, V., Chang, E.: Web of things as a framework for ubiquitous intelligence and computing. In: Proc the 6th International Conference on Ubiquitous Intelligence and Computing, pp 1–10 (2009)
11. Dou, D., Frishkoff, G., Rong, J., Frank, R., Malony, A. and Tucker, D.: Development of Neuroelectromagnetic Ontologies (Nemo): a framework for mining brainwave ontologies. In Proceedings of the 13th ACM SIGKDD international conference on Knowledge discovery and data mining, 270–279. San Jose, California, USA: ACM (2007)
12. Fisher, D.H.: Knowledge acquisition via incremental conceptual clustering. Mach. Learn. **2**(2), 139–172 (1987)
13. Francisco, V., Gervás, P., Peinado, F.: Ontological reasoning to configure emotional voice synthesis. In: Proceedings of the First International Conference of Web Reasoning and Rule Systems (Innsbruck, Austria, 2007), pp. 88–102. Springer, Berlin/Heidelberg (2007)
14. Frantzidis, C.A., Bratsas, C., Klados, M.A., Konstantinidis, E., Lithari, C.D., Vivas, A.B., Papadelis, C.L., Kaldoudi, E., Pappas, C., Bamidis, P.D.: On the classification of emotional biosignals evoked while viewing affective pictures: an integrated data-mining-based approach for healthcare applications. IEEE Trans. Inf. Technol. Biomed. **14**(2), 309–318 (2010)
15. Galunov, V.I., Lobanov, B.M., Zagoruiko, N.G.: Ontology of the subject domain. In: Speech Signals Recognition and Synthesis SPECOM'2004, 9th Conference Speechand Computer Saint-Petersburg, Russia (2004)
16. González, G., López, B., Rosa, J.L.D.L.: Managing emotions in smart user models for recommender systems. In: Proceedings of 6th International Conference on Enterprise Information Systems ICEIS 2004, vol. 5, pp. 187–194 (2004)
17. Gruber, T.: A translation approach to portable ontology specifications. In: Knowledge Acquisition, vol. 5, pp. 199–220 (1993)
18. Hudlicka, E., McNeese, M.D.: Assessment of user affective and belief states for interface adaptation: application to an air force pilot task. User Model. User-Adap. Inter. **12**, 1–47 (2002)
19. Jena: A semantic web Framework for java. http://jena.sourceforge.net/
20. Klein, J., Moon, Y., Picard, R.W.: This computer responds to user frustration: theory, design, and results. Interact. Comput. **14**, 119–140 (2002)
21. Koelstra, S., Muhl, C., et al.: DEAP: A database for emotion analysis using physiological signals. IEEE Trans. Affect. Comput., 99: 1–1 (2011)
22. Kunii, T.L., Ma, J.H., Huang, R.H.: Hyper world modeling. In: Proc the International Conference on Visual Information Systems (VIS'96), pp. 1–8 (1996)
23. López, J.M., Gil, R., García, R., Cearreta, I., Garay, N.: Towards an ontology for describing emotions. In: Proceedings of the 1st World Summiton the Knowledge Society (Athens, Greece, 2008), pp. 96–104. Springer, Berlin/Heidelberg (2008)
24. López, J.M., Gil, R., et al.: Towards an Ontology for Describing Emotions. Emerging Technologies and Information Systems for the Knowledge Society, vol. 5288, pp. 96–104. Springer, Berlin (2008)
25. Ma, J.H., Huang, R.H.: Improving human interaction with a Hyper world. In: Proc the Pacific Workshop on Distributed Multimedia Systems (DMS'96), pp. 46–50 (1996)
26. Ma, J.H.: Smart u-Things-challenging real world complexity. In: IPSJ Symposium Series, vol 19, pp. 146–150 (2005)
27. Ma, J.H., Yang, L.T., Apduhan, B.O., Huang, R.H., Barolli, L., Takizawa, M.: Towards a smart world and ubiquitous intelligence: a walkthrough from smart things to smart hyperspaces and UbicKids. Int. J. Pervasive Comput. Commun **1**(1), 53–68 (2005)
28. Maedche, A., Staab, S.: Ontology learning for the semantic web. IEEE Intell. Syst. **16**(2), 72–79 (2001)
29. Maedche, A., Staab, S.: Discovering Conceptual Relations from Text. Proc. ECAI 2000, pp. 32l–325 (2000)
30. Mandryk, R.L., Atkins, M.S.: A fuzzy physiological approach for continuously modeling emotion during interaction with play technologies. Int. J. Hum. Comput. Stud. **65**(4), 329–347 (2007)
31. Mathieu, Y.: Annotation of emotions and feelings in texts. In: Proceedings of the First International Conference ASCII 2005 (Beijing, China, 2005), pp. 350–357. Springer, Berlin/Heidelberg (2005)
32. McGuinness, D.L., van Harmelen, F.: OWL Web Ontology Language Overview. W3C Recommendation, 10 February 2004. Available at: http://www.w3.org/TR/2004/REC-owl-features-20040210/

33. Moore, P., Jackson, M., et al.: Fuzzy ECA rules for pervasive decision-centric personalised mobile learning computational intelligence for technology enhanced learning. In: Xhafa, F., Caballé, S., Abraham, A., Daradoumis, T., Juan Perez, A. (eds.). Springer Berlin, Heidelberg, 273: 25–58 (2010)
34. Mudie, P., Cottam, A., et al.: An exploratory study of consumption emotion in services. Serv. Ind. J. **23**(5), 84–106 (2003)
35. Nakaya, N., Kurematsu, M., Yamaguchi, T.: A domain ontology development environment using a MRD and text corpus. Proc. the Fifth Joint Conference on Knowledge-based Software Engineering Frontiers in Artificial Intelligence and Applications, pp. 242–251 (2002)
36. Nicholas, G., Stephen, H., Nigel, S.: Agent-based Semantic Web Services. Web Semant. Sci. Serv. Agents World Wide Web **1**(2), 141–154 (2004)
37. Peng, H., Hu, B., Liu, Q.Y., Dong, Q.X., Zhao, Q.L., Moore, P.: User-Centered Depression Prevention: An EEG Approach to Pervasive Healthcare, MindCare workshop in Pervasive Health 2011, Dublin, Ireland. pp. 325–330
38. Peng, H., Hu, B., et al.: An improved EEG de-noising approach in electroencephalogram (EEG) for home care. Pervasive Computing Technologies for Healthcare (Pervasive Health), 2011 5th International Conference on (2011)
39. Petrantonakis, P. C., Hadjileontiadis, L.J.: Adaptive extraction of emotion-related EEG segments using multidimensional directed information in time-frequency domain. Engineering in Medicine and Biology Society (EMBC), 2010 Annual International Conference of the IEEE (2010)
40. Quilan, R.J.: C4.5: Programs for Machine Learning. Morgan Kauffman, San Mateo (1993)
41. RDF Vocabulary Description Language 1.0: RDF Schema. http://www.w3.org/TR/rdf-schema/
42. Resource Description Framework (RDF): Concepts and Abstract Syntax. http://www.w3.org/TR/rdf-concepts/
43. Russell, J.A.: A circumplex model of affect. J. Personal. Soc. Psychol. **39**(6), 1161–1178 (1980)
44. Russell, S., Norvig, P.: Artificial intelligence: a modern approach. Prentice Hall, Englewood Cliffs (1995)
45. Sabeti, M., Boostani, R., et al.: Selection of relevant features for EEG signal classification of schizophrenic patients. Biomed. Signal Process. Control **2**(2), 122–134 (2007)
46. Shamsfard, M., Barforoush, A.A.: Learning ontologies from natural language texts. Int. J. Hum. Comput. Stud. **60**(1), l7–l63 (2004)
47. Stickel, C., Ebner, M., Steinbach-Nordmann, S., Searle, G., Holzinger, A.: Emotion detection: application of the valence arousal space for rapid biological usability testing to enhance universal access. In: Proceedings of the 5th International Conference on Universal Access in Human-Computer Interaction, pp. 615–624. (2009).
48. Stirbu, V.: Towards a RESTful plug and play experience in the web of things. In: Proc the 2008 IEEE International Conference on Semantic Computing, pp. 512–517 (2008)
49. Villon, O. Lisetti, C.: A user-modeling approach to build user's psycho-physiological maps of emotions using bio-sensors. Proc. IEEE Int. Workshop Robot Human Interactive Commun., p. 269 (2006)
50. Wehrle, T., Scherer, K.R.: Towards Computational Modeling of Appraisal Theories. Appraisal Processes in Emotion: Theory, Methods, Research, pp. 350–365. Oxford University Press, New York (2001)
51. Welbourne, E., Battle, L., Cole, G., Gould, K., Rector, K., Raymer, S., Balazinska, M., Borriello, G.: Building the Internet of things using RFID. IEEE Internet Comput. **33**(3), 48–55 (2009)
52. Xu, Z.M. Cao, X., Dong, Y.S. and Su, W.P.: Formal Approach and Automated Tool for Translating ER Schemata into OWL Ontologies. Proc. PAKDD 2004, pp. 464–476, (2004)
53. Zhong, N.: Impending brain informatics research from Web Intelligence perspective. Int. J. Inf. Technol. Decis. Mak. **5**(4), 713–727 (2006)
54. Zhong, N., Liu, J., Yao, Y.Y., Ohsuga, S.: Web Intelligence (WI). In Proceedings of the 24th IEEE Computer Society International Computer Software and Applications Conference (COMPSAC 2000), pages 469-470, IEEE Computer Society Press, Taipei, Taiwan, October 25–28, 2000
55. Zhong, N., Liu, J.M., Yao, Y.Y., Wu, J.L., Lu, S.F., Qin, Y.L., Li, K.C. and Wah, B.: Web Intelligence meets Brain Informatics. Proc. The First WICI International Workshop on Web Intelligence Meets Brain Informatics (WImBI 2006), pp. 1–31, (2006)
56. Zhong, N., Ma, J.H., Huang, R.H., Liu, J.M., Yao, Y.Y., Zhang, Y.X., Chen, J.H.: Research Challenges and Perspectives on Wisdom Web of Things (W2T). Journal of Supercomputing, Springer (2010)